A Review of Using Maximum Likelihood Classifier to Identify Land Use/Land Cover

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Abstract

Land Use and Land Cover (LU/ LC) map plays an important role in the digital society. These spatial data are applied to various application such as monitoring, planning, management and etc. In order to generate the high accuracy LU/LC map, the suitable classifier is an important factor. The objective of this study is to review the process of classification, showing the Maximum Likelihood Classifier (MLC) steps and give some examples of MLC which is the most popular image classifier. Class signature is a representative of each class. Each pixel whose probability is closed to specific class signature; it would be in that class. Accuracy assessment is in the form of an error matric table. Overall accuracy (OA) and Kappa coefficient of MLC are higher than the other classifiers. Examples of application on MLC are shown.

Keywords: *Error Matric Table, LU/LC, Maximum likelihood, Supervised Classification*

Introduction

Land Use and Land Cover (LU/ LC) generally refers to the categorization of human activities and natural elements on the landscape. The examples of LU/LC are (1) detecting the change of urban area in India [1], (2) LU/LC map of Nakhonnayok province of Thailand [2], Monitoring LU/LC with GIS techniques [3] and etc. Both of LU/LC can be obtained from the satellite image depending on scientific and statistical methods of the image interpretation [4]. Five processes of interpretation are pre-works by orienting the image with the base map, image reading, image measurement, image analysis and thematic map. In image analysis process, classification methods effect to the interpretation results, mostly [5-6]. There are traditionally two types of classification: unsupervised image classification and supervised image classification. Unsupervised image classification is working under an algorithm which determines and groups pixels in classes. It can be operated as an automatic classification. While, supervised image classification requires a training set as references for grouping the pixels. The training set which is selected from the image is operated as data entry to supervised classification algorithm or supervised classifier. Result is displayed in the form of class signatures. Rest of the image is determined and grouped in class based on each class signature [5] [7]. Commonly used supervised classifier parallelepiped (PP), minimum distance (MD), K-nearest neighbor (KNN) and spectral angle mapper (SAM) [5], [8–10]. Maximum

Likelihood Classifier (MLC), a traditional classifier, seem to be effective to the accuracy of interpreting the satellite image. Due to the formats of its class signature are the class mean vectors and the covariance metrics [11]. Both of them can be obtained from the quality of training set, probably the quality of the satellite image. Reports also show that a large number of users prefers to employ this MLC to their applications [6, 11]. The purpose of this paper is to review on using MLC to identify LU/LC. It consists of the processes of satellite image classification, MLC method, application of MLC and, finally, conclusion.

Satellite Image Techniques for Identifying Land Use and Land Cover

There are two types of classification: unsupervised classification and supervised classification. According to Figure 1, unsupervised classification techniques operate all analysis based on the image classification algorithms such as K-means and Iterative Self-Organizing Data Analysis Technique (ISODATA) [9], [12, 13].

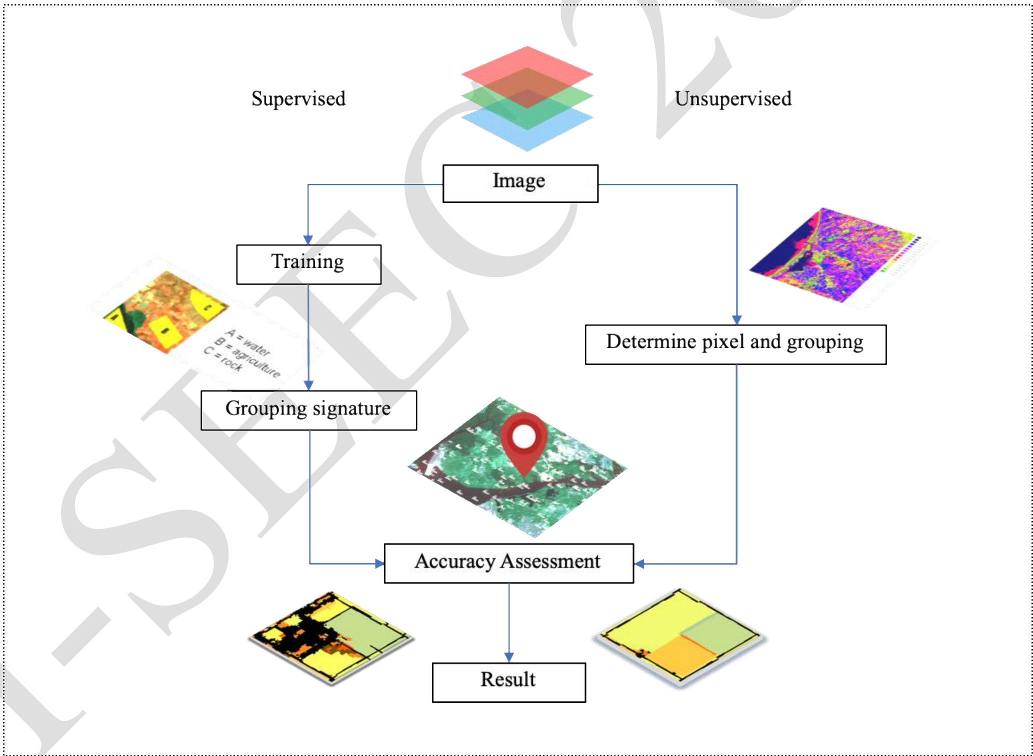

Figure 1 Supervised and unsupervised image classification

Supervised classifications analyst a satellite image, almost similar. Just only, this classification must generate the class signature from the training set before grouping the pixel into classes. Its accuracy depends on the quality of training set. In order to achieve the good quality of training set, the spatial resolution of the satellite image should be considered. Figure 2 shows the suitable scene cover size (Local scale, Medium scale and Global scale) and spatial resolution.

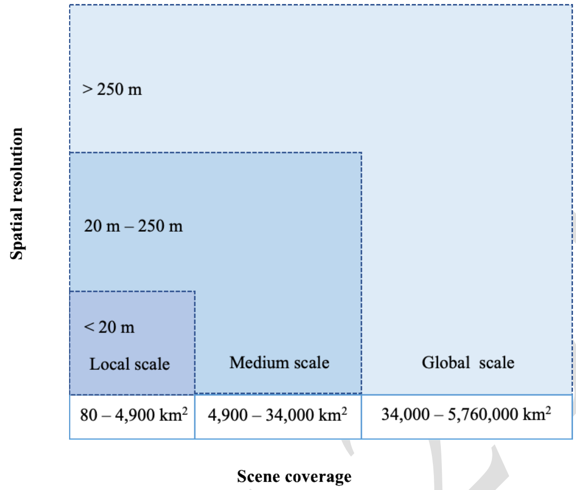

Figure 2 Scale of Satellite Image Data (Adapt from [14-15])

Satellite image of the local scale size can be obtained from IKONOS, SPOT 5, Quickbird are helpful. At the medium scale size can be obtained from Landsat TM/ETM+/OLI, Sentinel-2, and ASTER are the most used data, At a continental or global scale size can be obtained from MODIS, SPOT vegetation, Orbview-1, and AVHRR are prevalent and etc. [6], [14-15].

The last process of classification, the accuracy assessment, is calculated from an error matrix table as shown in Table 1.

Table 1- An error matrix [16]

		Ground truth classes			Total
		A	B	C	
Thematic map classes	A	35	2	2	39
	B	10	37	3	50
	C	5	1	41	47
Number of ground truth pixels		50	40	46	136

Classes of the thematic map are generated from the classifier. While, classes of the ground truth come from the field survey. Comparison the value of random pixel between these classes are filled in the table. Four assessment approaches are calculated from the error matric table: producer accuracy, user accuracy, over all accuracy and Kappa.

- Producer accuracy depends on the number of correct pixels in that class divided by the total number of pixels of that class (the corresponding column sum in Table 1(. It shows how much accuracy the classifier does. For example, fifty pixels of thematic map class A are selected. The result founds that class A, class B and class C are thirty-five, ten, and five pixels of the ground truth, respectively. Therefore, the value of producer accuracy of class A is thirty-five divided by total number of pixel and multiply by a hundred is equal seventy percent.
- User accuracy describes that how often the user does. To calculate the user accuracy, it does the same steps as the producer accuracy. Just only it is calculating based on the row of table. For example, thirty-five pixels of thematic map class A are selected. The result founds that class A, class B and class C are thirty-five, two, and two pixels of the ground truth, respectively. Therefore, user accuracy of Class A in Table 1 is thirty-five divided by total number of pixel and multiply by a hundred is equal eighty-nine percent.
- Overall corrected value is calculated from the corrected value on the diagonal direction. For example, one hundred and thirteen pixels of thematic map all class are selected. The result founds that class A, class B and class C are thirty-five, thirty-seven, and fourth-one correct pixels of the ground truth, respectively. Therefore, overall accuracy of error matrix in Table 1 are total number of correct pixels each class divided by total number of pixel and multiply by a hundred is equal eighty-three percent.
- Kappa coefficient assists in considering the consistency between the testing data and the reference data. It always considers Kappa with the overall accuracy. If both values of them are similar in the high direction, the classifier is considered good. In other cases, the classifier is not suitable for the classification [20].

Maximum Likelihood classifier

Classifier is the main factor for the image classification process. Using the proper classifier in the image interpretation will lead to a highly accurate LU/LC map [8], [21-22]. Maximum Likelihood Classifier (MLC) is one of supervised classifiers which widely applied to a variety of application. This method classifies the calculation of the probability for each given pixel in a class, in which the pixels are allocated to the class that has the highest probability. It calculates the mean vector and covariance matrix for training sample based on one assumption. That is each data class must have a normal distribution. According to Figure 3, the probability of pixel number 1 is closed to the group of class C. Therefore, pixel number 1 is classified as a member of Class C [23].

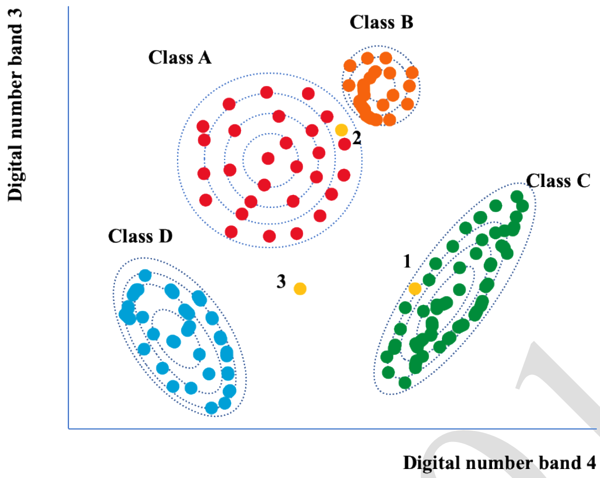

Figure 3 Maximum Likelihood Classifier

The normal distribution of MLC can be calculated as the following equation:

$$L_k(X) = \frac{1}{2\Pi^{\frac{n}{2}}|\sum k|^{\frac{1}{2}}} exp - \frac{1}{2} \left(X - m_k\right) \sum_k^{-1} (X - m_k)^t \tag{1}$$

X indicates as the image data of n bands. $L_k(X)$ represents the likelihood of X belonging to class k. m_k is mean vector of class k. $\sum k$ is the variance covariance matrix of class k [23]. There are various applications of LU/LC based on MLC as shown below.

- The study of monitoring about the change of LU/LC in Hawalbagh block, district Almora, Uttarakhand, India [3] - MLC was applied on the Landsat satellite images of two different periods: 1990 and 2010. Results showed that the image was divided into five classes including: vegetation, agriculture, barren, built-up and water body. In 2010, the number of vegetation and built-up area were more than their numbers in 1990. While, the number of agricultures, barren land and water body area were less than their numbers in 1990. Survey result of the year 2010 also showed in the same direction.
- Detecting and learning the agriculture situation of Nakhon Nayok, Thailand [2] - this study determined the class of LU/LC based on MLC. The Landsat satellite images of 2004 until 2015 were used as the primary resources. The satellite image was divided into five classes namely water, agriculture, urban, bare soil, and forest. Result showed as the series of LU/LC changes during these 10 years.

- Monitoring the LU/LC of Selangor, Malaysia [11] – a comparative study was conducted based on ISODATA classifier and MLC. Clustering method of ISODATA could generate eight classes: urban, industry, oil palm, dry-land forest, coastal swamp forest, cleared land, water and sediment plumes. While, MLC classified it into eleven classes more than ISODATA and they were coconut, rubber and bare land. MLC has a higher classification accuracy than ISODATA.
- Pixel-based classification analysis of LU/LC using Sentinel-2 and Landsat-8 data in Zonguldak, Turkey [25]. – Two satellite images of Sentinel-2 and Landsat-8 were analyst for LU/LC map. Based on MLC, there were five classes: water body, settlement, forest, bare-land and vegetation. Accuracy assessment of these two types of image tended to the good direction. However, the Sentinel-2 presented the OA higher than Landsat-8 data. Due to, Sentinel-2 had-a spatial resolution higher than Landsat 8.
- Island management in Italy [26] - Landsat satellite images were analyzed for detecting the change of small island areas. Using MLC, there were four classes in these satellite images: urban, bare soil (with rocks), sparse vegetation and dense vegetation. The accuracy assessment was based on field survey. Results showed that the OA is 85 percent and the evaluation of the specific map accuracy received guarantees the quality of the results at the level of 1: 25,000.
- A LU/LC map of Prahova Subcarpathians, Romania [27] – Two classifiers (minimum distance classifier and MLC) were applied on Landsat-8 satellite images of the local area in Prahova Subcarpathians. Result showed that MLC displayed the LU/LC map with high accuracy, while, the other displayed the LU/LC map with low accuracy.
- Finding the appropriate classifier for Ralegaon Siddhi watershed, Ahmednagar district of Maharashtra state, India [17] – the satellite image of IRS-1C LISS-III were used in this study. Four classifiers (MLC, box, minimum distance and mahalanobis) were applied. Five classes (agricultural land, shrubs, water body, wasteland and barren land) were assigned for each classifier. Ground investigation had been conducted to check and assess the accuracy of classification. Result showed that the accuracy assessment of MLC, mahalanobis, minimum distance and box were 88.52, 84.26, 81.85 and 58.15, respectively. Kappa value of these classifier also revealed in the same direction with the accuracy assessment. Hence, MLC could be the most appropriate classifier for this study.

According from above examples, LU/LC map is classified as basic spatial information for managing and deciding in several areas such as city management, forest management, and etc. The accuracy assessment of MLC is higher than the other assessments. The OA value is increasing along with Kappa coefficient value. Hence, LU/LC map is generated with high accurate and consistency. It can be said that MLC is classified the most suitable classifier for generating LU/LC map.

Conclusion

In order to select the suitable classifier, many factors must take into account. They are area size and spatial resolution, classifier and accuracy assessment of classification. Study area may lead to specify the scales of satellite image which are local scale, medium scale and global scale (Figure 2). To interpret a satellite image, two classification methods (supervised method and unsupervised method) are considered. Pixels on a satellite image may be identified in any information depending on the classification. Classification is a process of image analysis which determines, and groups related pixels in each class. Supervised classifiers, MLC, PP, MD, KNN, SAM and Maharanobis, are often applied due to the training process can guarantee the class signatures are actual representative of the particular area. Classifier performs well depending on sampling of training areas, statistical of sample areas (e.g. spectral signature, variance, correlation), and its own algorithm. An error metric table is used to calculate four assessment values: producer accuracy, user accuracy, over all accuracy and kappa. MLC are the most utilized classifier as shown in Section 3, due to the OA value and Kappa coefficient value is higher in the same direction. While, these values of other classifiers are lower.

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